On the Possibility of Developing a Brain-Computer Interface (BCI)

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Technical Report (finished in 2001)

Abstract: In this report, it will be commented on the question, if it is possible to develop a brain-computer interface, i.e. a system that analyzes the brain-electrical activity of a subject, tries to find out (or at least to get an idea of) the subject's intention, and generates output commands controlling an appropriate output device accordingly. This includes a discussion of the pros and cons of such an EEG-based user interface, covering all aspects of this topic (without any implied claim to be complete) – ranging from the EEG input, over the processing stage, all the way to the corresponding output signals. Examples of working BCI's will be mentioned and their performance will be (subjectively) evaluated.

1 Introduction

The ability to control or move certain objects by mere thought is an attribute of (in many cases alien) lifeforms that is often portrayed in science fiction movies. The issue of turning this idea into science fact has become more and more popular over the last couple of years. However, the prosaic, scientific view of this does not involve any mystic, telepathic power (of course). Scientists are trying to devise systems that record and analyze the brain-electrical activity (EEG) of a subject – represented by tiny voltages (i.e. numbers), measured at consecutive points in time – with the help of a computer. Since such a system tries to somehow convert the thoughts of the human being in front of the computer into a machine-readable format, it is called a *brain-computer interface* (or, shorter, BCI – see fig. 1).

The idea of direct brain-computer communication was first mentioned in (Vidal 1973), and nowadays, more than 20 research groups all over the world are working on this problem (see Wolpaw *et al.* 2000*b*). Numerous articles in newspapers or scientific magazines (e.g. Fey 1995, Lusted and Knapp 1996, Diedrich 1999) are presenting different approaches and first promising results from those groups. In this context, even the slightest hint at a working device (though extremely slow and not terribly accurate, with often immense hardware requirements) is applauded as a huge success.

This report comments on the entire range of aspects of a BCI, and since developing a BCI combines a huge variety of different disciplines (such as medicine, biology, computer science, physics, mathematics, electrical and mechanical engineering, ...), that "range" is terribly large. It is therefore virtually impossible to keep track of everything written and published in this field, and any comprehensive work on BCI's (which this report is intended to be) necessarily has to be incomplete.

However, in order to be as universal as possible, I will take a close look at the following questions from different angles.

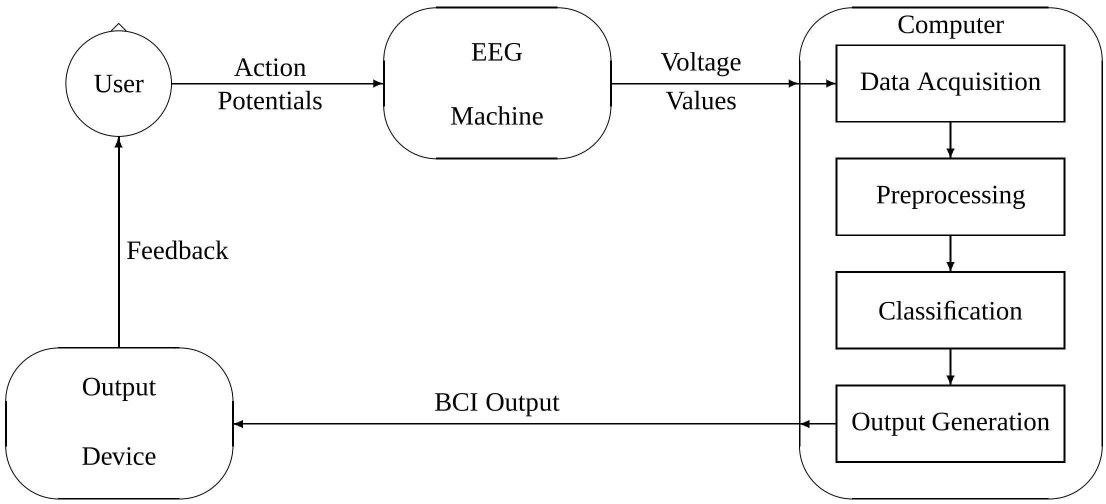

Figure 1: Schematic Sketch of a BCI

- *What* is *the EEG anyway?*
- *What are EEG signals "normally" used for?*
- *Why and how can they be used for a BCI?*
- *How can a computer "understand" EEG signals?*
- *What are possible applications?*
- *How about the quality and accuracy of currently working BCIs?*

It is evident that rating and evaluating different approaches can never be objective (just like the review of a theater play is not objective) – it will always reflect the author's personal point of view.

The rest of this report is organized as follows. After some remarks on the use of BCI's in general, the electroencephalogram – what it looks like, how it is measured, what it is used for, what information it contains, etc. – is described in detail in section 3. Section 4 talks about the philosophy behind using EEG signals for a user interface. At first, EEG signals are nothing but numbers – they have to be interpreted to make any sense to a computer. This is the topic of section 5. Classification with a neural network, which will be dealt with in detail after that, enables the computer to "understand the thoughts" of the user (to a very limited extent). Section 7 is devoted to the possible applications of a BCI – since influencing computer functions with mere thoughts is nice, but not the original purpose, one of the most important questions is what the output of the BCI is controlling in the first place. Section 8 will explain why devising a BCI (that actually works!) is extremely difficult. Before concluding this report with a short summary, some of the systems in use today will be described and evaluated.

2 General Remarks

A brain-computer interface is intended to enable its user to communicate with a computer by mere thoughts. There are (at least) two reasons why research on this new way of communication – as opposed to the standard input methods involving keyboard and mouse (which works well for most people) – becomes more and more popular.

On the one hand, using a mind-controlled input device requires almost no effort. It needs no muscle contraction, and the user "only" has to have a clear mind. This makes persons with severe physical disabilities the main target

group. Especially persons suffering from the so-called "locked-in" syndrome are the ones that need such a device, since they have almost no motor control (apart from maybe unreliable control of some facial muscles), which means that they can neither talk, nor move feet, legs, arms or hands.

The term "*physical* disability" implies that those persons don't have any *mental* problems, which is particularly true for locked-in patients (a situation, where *a person's mobile mind is locked in an immobile body*). Therefore, a BCI can be operated by a physically handicapped – sometimes it is even their only chance to directly influence their environment.

On the other hand, controlling certain computer functions by thoughts may seem to be a "more natural" way of communicating with a computer. Everyone who uses a computer sufficiently often has probably already encountered the situation, where *the mind passes the hands*, i.e. the user has already decided on what to do, but the process of realizing this decision (by typing this and that, by clicking here and there) just takes ages.

When a (healthy) human walks, he or she does not need to decide on the correct order of contracting every single muscle involved in the action of walking. According to the motor program theory of Schmidt (1982), it suffices to "execute" or *recall* previously recorded (*learnt*) macros (probably stored in the cerebellum) simply by issuing the (mental) command to walk.

Similarly, it might be enough to only think of something for selecting a sequence of appropriate computer functions. However, there is one major difference. The macro or sequence executed with the help of the BCI is not fixed, but dynamically dependent on the user's thoughts.

Furthermore, a BCI that would really be able to generate such a sequence of computer actions must be able to literally read the thoughts of the user, e.g. if the user thinks about two objects O_1 and O_2 with a distance of 5 yards in between, the system has to retrieve that information exactly (and distinguish it from a 6-yard-distance). As we will see below, it is (almost) impossible – or at least extremely improbable – that a system which fulfills these requirements can ever be constructed. Furthermore, the goal in BCI research is much less utopian. This topic will be dealt with in further detail in section 4.

3 The Electroencephalogram (EEG)

This section takes a close look at the electroencephalogram (EEG), which is the foundation of current BCI research. First, the biology of the brain is introduced, and the interactions of the nervous cells are briefly explained. Secondly, the question how the EEG looks like will partially be answered. Finally, some thoughts on what the EEG is used for, i.e. what can be seen in it, will conclude this section.

3.1 Some Words on the Biology of the Brain

The human brain contains a huge network of billions of nervous cells (also called *neurons*). A typical neuron is depicted in fig. 2 (see also Alberts *et al.* 1989).

A neuron consists of several dendrites (often called *dendritic tree* because of its typical shape), a cell body (or *soma*), and an *axon*, which may be as short as $100\mu m$ (in the case of neurons in the central nervous system) and sometimes as long as $1m$ (e.g. in the case of some peripheral nerves going to muscles in the leg). The dendrites of a neuron are connected to the axons of several other ("predecessor") neurons, and the contacts between axons and dendrites are called *synapses*.

One may think of a neuron as a simple binary processing unit[1]. In this respect, the dendrites represent some sort of input channels, while the axon carries a binary output information. Each neuron calculates a weighted sum of the input signals coming from its predecessors (where the weights are "stored" in the synapses, which may be either *excitatory* or *inhibitory* with varying strength) and determines, whether or not this sum exceeds a certain threshold. If so, the neuron outputs a "1" down its axon – the neuron is then said to be "firing".

Signal transmission in the brain involves the displacement of differently polarized ions (see Hartmann *et al.* 1996), and therefore, action potentials coming from firing neurons generate electric fields. If a human thinks about a certain thing, hears, sees, does or says anything, has certain emotions or simply: if he or she is alive, different neurons get activated and interact with one another.

[1] This view is not totally exact in some cases, and it surely represents a coarse simplification, but it facilitates understanding.

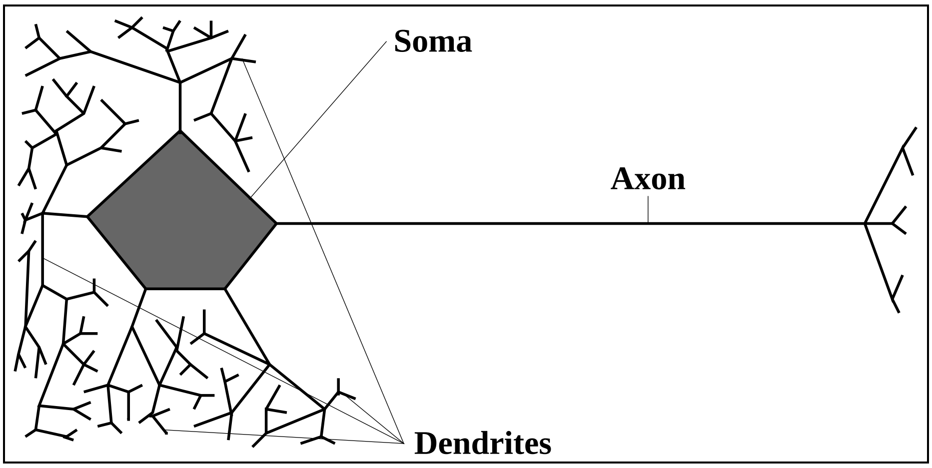

Figure 2: A Typical Neuron (Simplified)

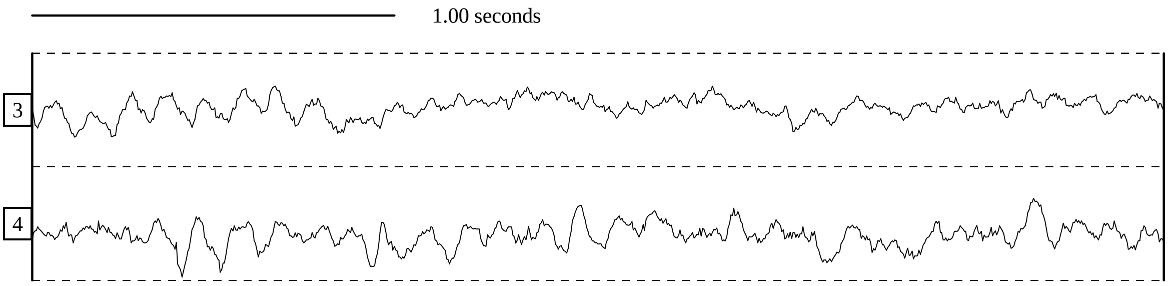

Figure 3a: 2 Channels of EEG Reading with Closed Eyes

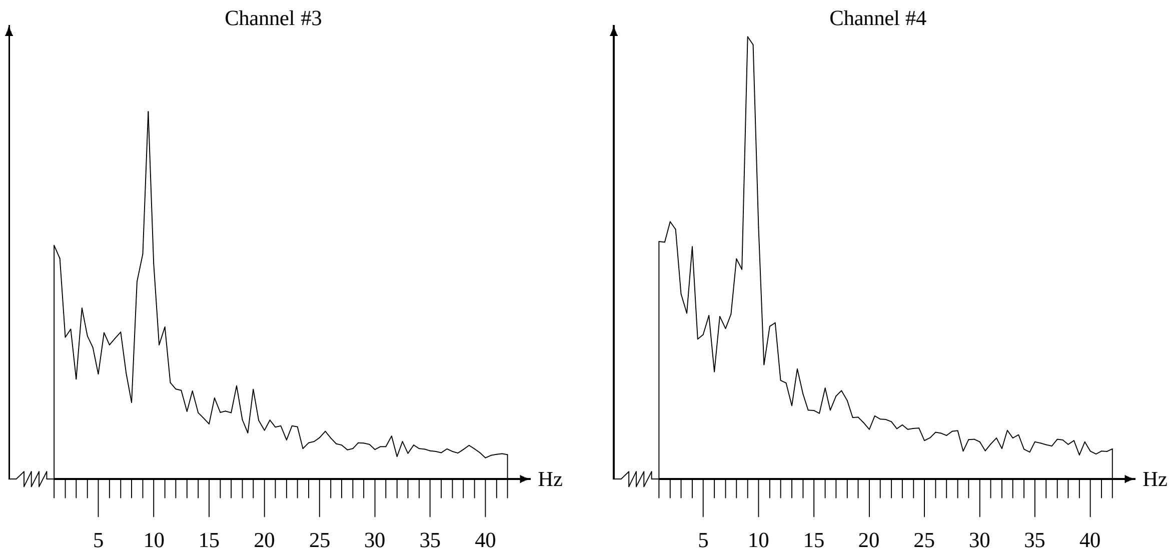

Figure 3b: Frequency Spectrum (Closed Eyes)

3.2 Shape

Since any neuronal cerebral activity generates (tiny) voltage potential changes, the process is measurable to some extent. Measuring this can be done non-invasively – e.g. with an electroencephalogram (EEG) or a magnetoencephalogram (MEG) – or invasively – with an electrocorticogram (ECoG, Levine *et al.* 2000) or by implanting special electrodes that can reply to *single-unit activity* (Kennedy *et al.* 2000, Isaacs *et al.* 2000). Evidently, the non-invasive methods are to be preferred because of the medical risk inherent in surgical implantation. Since MEG demands much more expensive equipment, EEG is the method of choice for the majority of the BCI research groups. In the following, this report will exclusively concentrate on EEG-based non-invasive systems.

EEG measures the electrical potential with the help of several electrodes at predefined points on the skull (for electrode positions, see Jasper 1958), with one additional electrode (sometimes between the eyes above the nose, sometimes at one of the ears) to ground the subject. The differences[2] between values belonging to two different sites are calculated (so as to somehow filter out external influences affecting both electrode sites), and the results get amplified by a factor of about 10^4 (which brings the values into the range of about $1V$).

Unless a person is dead, brain-electrical activity is *always* present, i.e. that person's EEG (voltage versus time) curve constantly varies. Apart from artifacts because of muscle contractions or eye movements etc., the signals exhibit contributions from frequencies between 0.5 Hz and about 40 Hz. Due to historical reasons, the range [0.5 Hz..30 Hz] is subdivided into the four frequency bands alpha, beta, theta, and delta (see table 1).

Frequency Band	**Range**
Alpha (α)	$8 - 13$ Hz
Beta (β)	$14 - 30$ Hz
Theta (θ)	$4 - 7$ Hz
Delta (δ)	$0.5 - 3$ Hz

Table 1: Relevant Frequency Bands (according to Klinke and Silbernagl 1996)

The contribution of each frequency band to the overall EEG curve depends on the respective situation. For instance, healthy subjects often reveal a predominance of the α-rhythm, when the eyes are closed (see figs. 3a and 3b). Opening the eyes then usually causes a blocking of the α-band, while other frequencies then become more dominant (see fig. 4a and 4b).

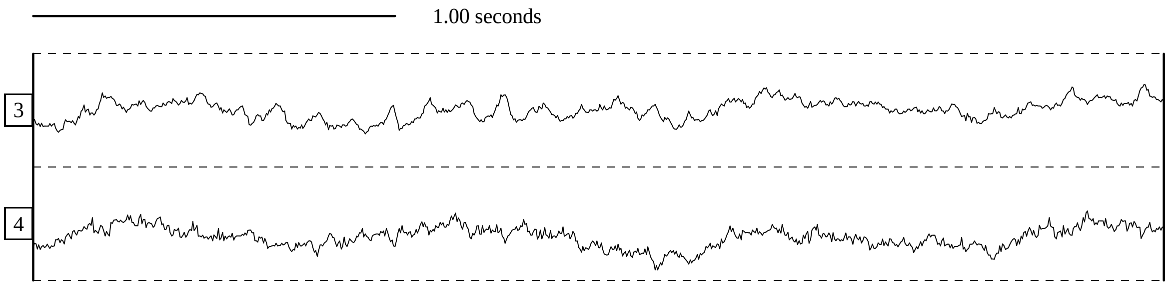

Figure 4a: 2 Channels of EEG Reading with Open Eyes

[2]For EEG recording, one of the following two procedures may be adopted: either all but one electrode are measured against the same single reference electrode (often placed on the unused ear lobe), or the electrodes are pairwise measured against each other.

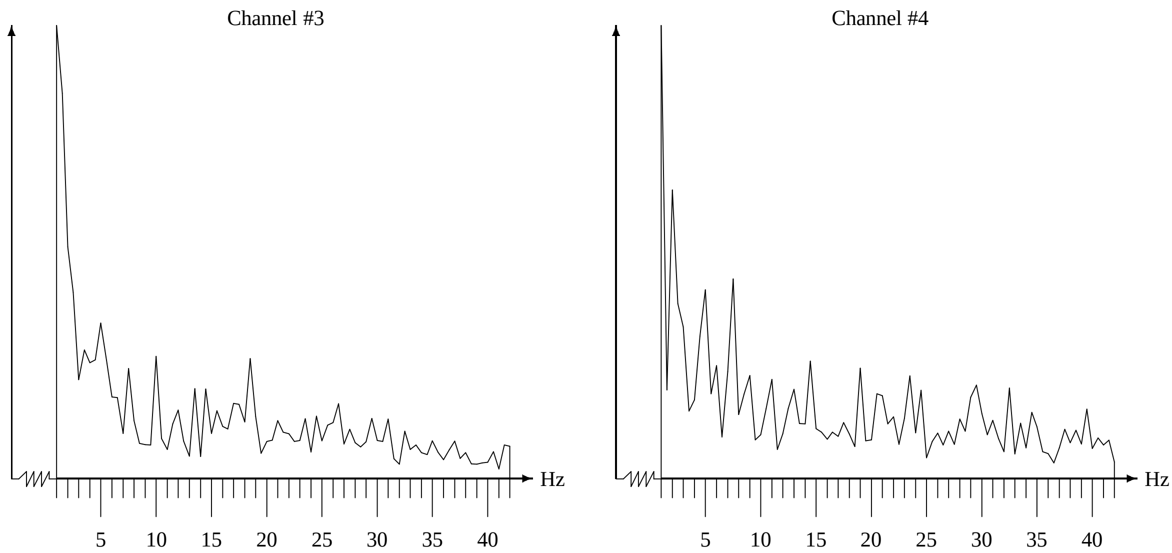

Figure 4b: Frequency Spectrum (Open Eyes)

3.3 Contents

Probably the most common clinical application involving the EEG is represented by the diagnosis and therapeutic treatment of certain neurophysiological disorders like epilepsy (Mirbagheri *et al.* 1992, Ko *et al.* 1998). The EEG curve of a patient suffering from a correponding disease[3] reveals certain characteristic elements and can thus be used to detect the disorder. For instance, the trace of an epilepsy patient contains complexes consisting of a spike followed by a slow wave (Saevarsson *et al.* 1997), which can be detected e.g. with the help of statistical classification.

Apart from surgery, *biofeedback* – a procedure where a patient sees his or her own biosignals, such as brainwaves (EEG), eye movements (EOG), and heart-beat (ECG), on a computer screen online and learns to somehow control them – is often used in therapy (e.g. Kotchubey *et al.* 1999).

Another common application of the EEG is the objective assessment of the vigilance of a patient (e.g. Offenloch and Zahner 1988). This includes the characterization, analysis, and detection of *sleep stages* (Roberts *et al.* 1995, Grall-Maës and Beauseroy 1998, Moreno *et al.* 1998).

Poulos *et al.* (1999) make use of the fact that the EEG carries certain genetic information and show that it is possible to develop a person identification test based on EEG signals. In other words, certain EEG features depend on the individual subject, and the EEG can lead to some sort of "genetic fingerprint". Although the results are not *perfect* (yet), the idea is extremely interesting.

As one might have already guessed from the mention of biofeedback above, there is a lot more to EEG than just answering the questions whether or not a person is suffering from epilepsy or whether or not a person has lost consciousness. In addition to any (neuro-)physiological phenomena, the brainwaves depend on thoughts and mental activities. The EEG signal is definitely not "chaotic" and chances are that it can even be influenced and controlled at will.

It can be shown that cognitive processing causes systematic variations of the brainwaves. For instance, Skrandies (1998) examines the effect (and there really is one) of semantic processing on the EEG by presenting words belonging to different semantic word classes on a computer screen to several subjects. This resulted in differences in the EEG data – concerning scalp topography, latency and amplitude – depending on the semantic meaning of the visual stimuli.

[3]Epilepsy itself is not a disease, but a symptom caused by several diseases (see Marchesi *et al.* 1997).

Mölle *et al.* (1996) shows how to distinguish between two types of creative thinking, and in (Pauli *et al.* 1998), it is demonstrated, how speed and accuracy of mentally solving simple arithmetic problems varies with certain self-initiated brain states. Other examples showing that the EEG really depends on mental activity and that it is possible to intentionally change one's brainwaves are presented in section 9.

4 The Idea

Especially certain "yellow press" articles or various science fiction movies want to make us believe that surgically interfacing nervous cells with computer chips is no problem (in a not too distant future). A typical example is the replacement of Luke Skywalkers hand (which he lost in a fight against his father) by a near-perfect artificial prosthesis at the end of the second "Star Wars" movie ("The Empire Strikes Back"). In this respect, one might think of a brain-computer interface as a device that is entirely realized in hardware, where the application involves an operation providing a "surgical connection" between the brain of the user and a (probably remotely operated) computer.

To be polite, this is a *very futuristic and optimistic* view of the progress in medicine. Our current knowledge of the functions of the brain and the interactions of the nervous cells is extremely limited. Moreover, microscopically identifying individual neurons, determining their exact functions, and connecting them to a computer chip, is something that not even a team of the best surgeons around the globe can do. "Never" might be the wrong word, but based on present knowledge, it seems to be *highly unlikely* that this ever becomes possible, and it is no wonder that the first positive results concerning attempts to make paraplegics walk again originate from an approach involving the external stimulation of leg muscles(see Brand 2000), <u>not</u> relying on surgically bridging the gap between wounded nervous tracts.

Since the interactions of neurons are based on electrical processes resulting in measurable signals, an alternative (operation-free) possibility for devising a brain-computer interface exists. It is based on the monitoring of the brain-electrical activity of the user (which is influenced by his or her thoughts) and extracting commands to control computer functions. This concept characterizes the usual type of system that is referred to by the term *brain-computer interface* (BCI).

The voltage produced by a single firing neuron is so tiny that it is hardly possible to identify it in the normal EEG, let alone isolate the signal from all other action potentials. So even if we knew the meaning of the firing of each and every neuron (and we are far away from that), the exact interpretation (the literal translation) of a "thought" would not be possible, since only the common firing of larger assemblies of neurons can be seen in EEG traces (see also Wolpaw *et al.* 2000*a*).

Therefore, a BCI is <u>not</u> intended to be a device enabling its user to literally talk with a computer by thinking (in a similar way he or she would talk with another person by articulating words). Rather, the idea is to find certain patterns in the *input signal* – i.e. the raw EEG or one of its derivatives, e.g. the frequency spectrum, the wavelet transform, . . . – associated with a particular thought.

There are different problems that have to be solved – best characterized by the following questions.

1. What type of input signal (or what frequency range) should be used?
2. Where to place the electrodes?
3. What mental activity (what thought) produces the best results?
4. What do the patterns look like and how are they recognized?

The first two questions can be tackled by a "brute force approach" – like the one described in (Pfurtscheller *et al.* 1996*a*) – where several frequency bands and electrode positions are used. Optimum conditions are then determined by simple comparison.

Unfortunately, the third question on the type of mental activity or thought is probably the most important, yet most difficult one (and having an answer for that question is a prerequisite for the first two, by the way). The goal is to find something, that the user can reproduce reliably, fast, and arbitrarily ("on demand") which leads to

input signals that differ from those produced by other thoughts. Furthermore, it is very likely that this question is user-dependent, i.e. two people probably have to employ different mental activities for equally good results.

For example, in order to move a cursor on a computer screen to the left or to the right, it is necessary to find at least two different classes of thoughts (producing different patterns). Let us suppose we want to verify if thinking about moving the left and right index fingers will do. For the two corresponding thoughts to be appropriate for the job, the following requirements have to be met.

- Thinking about moving the left index finger will always generate sufficiently similar patterns – as does thinking about moving the right index finger.
- The patterns produced by both thoughts are sufficiently different (in order to be discernible).

Additionally, we have to bear in mind that this verification always includes the other questions mentioned above on the nature of the input data and on pattern recognition. Therefore, the entire process is multidimensional and requires a lot of "trial-and-error" search.

The main goal in developing a BCI is to find a way to discriminate (at least) two mental activities (simple relaxation, where the user tries to "think about nothing", might be one of them). The patterns extracted from the input signal are assigned to different classes (probably with the help of a neural net classifier, see section 6), and the minimum number of reliably discernible classes is two (e.g. Wolpaw *et al.* 2000*b*), since any human-computer interaction can be realized with a sufficiently large number of consecutive yes-no-questions (which requires two classes, one for "yes" and one for "no").

5 Preprocessing the Data

The main task of a BCI is to recognize patterns by interpreting sequences of numbers. This automatically raises the question what these numbers are, i.e. where they come from. The BCI is confronted with (integer) values coming out of an analog-to-digital converter – digitizing the output of an EEG machine connected to the user – or a digital EEG machine at a rate of (typically) 100 – 300 Hz per channel as raw input data. As there are usually up to 32 channels, the system has to deal with up to 10000 values per second.

Shoveling this huge amount of data in a neural net classifier might be a simple and the most straightforward way of analyzing the data. However, the classifier will most probably not find anything. In order to receive useful results, those parts containing the most important information – which is also a matter of representation – have to be extracted. Besides, since the raw data may be contaminated by all sorts of artifacts, it is not very wise to use them directly as input signal for the classifier.

This section introduces different methods developed to represent the data and to extract the important information from it. The methods include the Fast Fourier Transform (FFT), the Wavelet Transformation, Blind Signal Separation, and EOG Monitoring.

5.1 FFT

In order to analyze the data signal for its frequency content, it has to be converted from the time domain into the frequency domain. This can be accomplished by applying a mathematical method known as Fourier Transform.

The Fourier Transform is based on the assertion that any 2π-periodic function $f(x)$ is the superposition of sine and cosine functions, i.e. can be written as (see Graps 1995)

$$\hat{f}(x) = a_0 + \sum_{k=1}^{\infty}\Big(a_k \cos(kx) + b_k \sin(kx)\Big).$$

The coefficients a_k and b_k (which are the calculation result of the Fourier Transform) denote the amplitudes of corresponding sine and cosine oscillations – the *basis functions* in this transformation. Therefore, the representation $\hat{f}$ directly contains information about the contribution of every frequency to the function $f(x)$.

In the context of EEG analysis, the Fourier Transform is applied (once for each channel) to a finite number of discrete data points belonging to successive (sometimes overlapping) segments of equal length. For the calculation,

the segment length l (in seconds) is mapped onto the range $[0..2\pi]$, so for example, a_{k_0} and b_{k_0} correspond to the frequency k_0/l Hz (since the functions $\cos(k_0 x)$ and $\sin(k_0 x)$ describe k_0 complete oscillations in $[0..2\pi]$, i.e. in l seconds).

It is customary to combine the two coefficients, so as to get only one amplitude value per frequency, and since the sines and cosines are phase-shifted basis functions (with vanishing inner product – just as the orthogonal basis vectors in Euclidean space) the compound value

$$\sqrt{a_{k_0}^2 + b_{k_0}^2}$$

seems to be the most adequate measure for the amplitude of k_0/l Hz – at least that's what's used in the calculation of the frequency spetra depicted in sections 3 and 8.

The term *Fast Fourier Transform* now refers to the specific algorithm employed when calculating the Fourier coefficients, which requires the number of data points per segment to be a power of 2 and which involves the temporary use of complex numbers (for a more detailed explanation of the underlying mathematic theory, see Törnig and Spellucci 1990). The effect of this algorithm is that the frequency spectra (as one possible data representation) can be generated online – the general algorithm for the so-called Discrete Fourier Transform would require way too much computation time, even for the most powerful computer.

One more thing shall be added. The resulting coefficients represent only a finite approximation of the function $\hat{f}$ detailed above. Especially for "non-periodic" segments[4], the Fourier series is not totally suitable. However, as can be seen from the frequency spectra in this report (in particular the exact 50 Hz peak in fig. 8b), the precision error introduced by this is not too severe.

5.2 Wavelet Transform

The Fourier Transform suffers from a number of problems. For example, the transformation is not localized in time. This means that there is no temporal connection between the frequency spectrum and the EEG signal producing it – at least not within a converted segment. If at some point in time, the EEG signal exhibits a small local variation, the frequency spectrum of the entire segment is globally changed, and there is no way to deduce from the spetrum alone when exactly the variation took place.

Of course, it is possible to introduce some sort of localization by reducing the segment length l – that way the *temporal resolution* is improved. The bad news is that the *frequency resolution* is given by the expression[5] $1/l$, so l cannot be reduced arbitrarily. The localization issue can additionally be addressed by analyzing overlapping segments every $r \cdot 1000$ milliseconds with $r < l$ ($1/r$ shall be called *overlapping rate*). However, this improves the situation, but still is no ultimate cure, since the temporal delay (the time span until the system reacts) still depends on l.

Besides, the Fourier Transform has the problem that the resolution is predetermined. The values of r and l can be chosen beforehand, but then, during the actual operation of the system, temporal *and* frequency resolutions are fixed. However, it might be desirable to recognize sharp high-frequency discontinuities, while at the same time examining the lower frequencies in detail. This requires looking at the signal at different scales and multiple resolutions, which can be done with the help of the Wavelet Transform.

The Fourier and Wavelet Transforms have some very strong similarities, while one distinction are the basis functions. The basis functions of the Wavelet Transform – the *Wavelets* – are not any periodic sine and cosine waves that stretch out to infinity, but "small waves" with compact support, being non-zero only in a finite interval. The resolution feature comes from the set of all basis functions involved in any particular wavelet analysis, which comprises scaled, contracted, and dilated versions of a so-called *mother wavelet*.

Wavelets have received more and more attention in the near past from scientists in numerous application fields, such as data compression, EEG analysis human vision, image processing, music, radar, acoustics, and treating noisy data. For instance, Wavelet Analysis was used in (Hazarika *et al.* 1997) to distinguish between EEG traces originating from subjects suffering from different neurological disorders, in (Saevarsson *et al.* 1997, Zhang *et*

[4]This not only means that the first and last data points in a segment are unequal, it also refers to the nature of the signal as a whole.

[5]This follows directly from the definition of $\hat{f}$ in the previous subsection.

al. 1999, Goelz *et al.* 1999) for he automatic detection of epileptiform waves in the EEG, and in (Dixon and Livezey 1996) to examine the effects of prenatal drug exposure on the EEG in rats.

Jahnke (1995) introduces an implementation that uses wavelet analysis for filtering EEG signals in order to emphasize certain elements in the signal. Cody (1992) presents the theoretical foundations of wavelets in close detail, and a comprehensive work (also talking about the historical perspective) is (Graps 1995).

5.3 Other Methods

The EEG signal – no matter how many channels are involved – is always a mixture of a large number of individual signals. This is due to two reasons. First, one single action potential cannot be registered, so any voltage potential change contained in the EEG recording is the effect of thousands of neurons firing simultaneously. Second, and more important, the recordings from each electrode are influenced by multiple (supposedly independent) sources in the brain, e.g. an activity in the auditory cortex not only affects the electrodes directly above this brain area, but all other recording sites as well.

The goal of *Blind Signal Separation* is to isolate those independent signal sources, and applying further processing only to a limited number of isolated signals promises to yield a much better classification performance. Various methods for accomplishing this task have been developed, and it is beyond the scope of this report to introduce them in detail. The two keywords *Decorrelation* (Chan *et al.* 1995) and *Independent Component Analysis* (Makeig *et al.* 1997) shall merely be mentioned – the interested reader is referred to the literature.

Another alternative for the representation of the input data is to replace the actual voltage values with certain coefficients obtained by applying a method known as *autoregressive (AR) modeling*. The basic idea is to predict a value of the EEG time series with the help of a linear combination of n preceeding values, where n is called the *order* of the AR model (see Anderson and Sijerčić 1996, Peters *et al.* 1998, Anderson *et al.* 1998). With $\hat{x}(t)$ being the prediction of the time series at time t and $x(t-i)$ being the *actual value* of the series at time $t-i$ (with $i = 1, \ldots, n$), this translates into the following formula.

$$\hat{x}(t) = \sum_{i=1}^{n} a_i x(t-i).$$

The coefficients $a_i (i = 1, \ldots, n)$ minimizing the summed squared error of this prediction

$$\sum_t (\hat{x}(t) - x(t))^2$$

are called the AR coefficients of this model[6] (the parameter t in these equations ranges from the beginning to the end of a segment). The AR coefficients within an EEG segment may be used as input data for the classifier – representing that particular segment. Polak and Kostov (1998) has found out that the use of AR coefficients allows shorter segments, which reduces the system delay, while still yielding better performance than the use of Fourier coefficients.

Finally, some words on the noisy nature of the EEG signal and possible solutions for this problem shall be added. Any blink with the eyes, any head movement, any teeth gritting – in short: any conscious muscle contraction whatsoever (breathing probably being an exception) – causes artifacts in the EEG signal. Furthermore, the result of moving the eyes is not as clear as a muscle contraction artifact, but it still changes the signal considerably – rendering the corresponding data segment useless for further analysis. Moreover, often only contributions from certain frequency bands are used – in such a case, the rest of the signal has to be regarded as noise, too.

There are two ways to deal with the problem of noisy segments: filtering the signal or discarding the segments. For the filtering solution, different methods or digital filters can be used (e.g. McFarland *et al.* 1997, Carballido *et al.* 1999), but, in most cases, this is not applicable to artifact-contaminated segments. For treating those, the signal or a simultaneously recorded EOG (monitoring eye movements) is inspected (in a suitable way), and “polluted” segments are sorted out – this of course only makes sense if the quota of unpolluted segments is not too small!

[6] How they are computed exactly cannot be subject of this report – here again, the interested reader is referred to the literature.

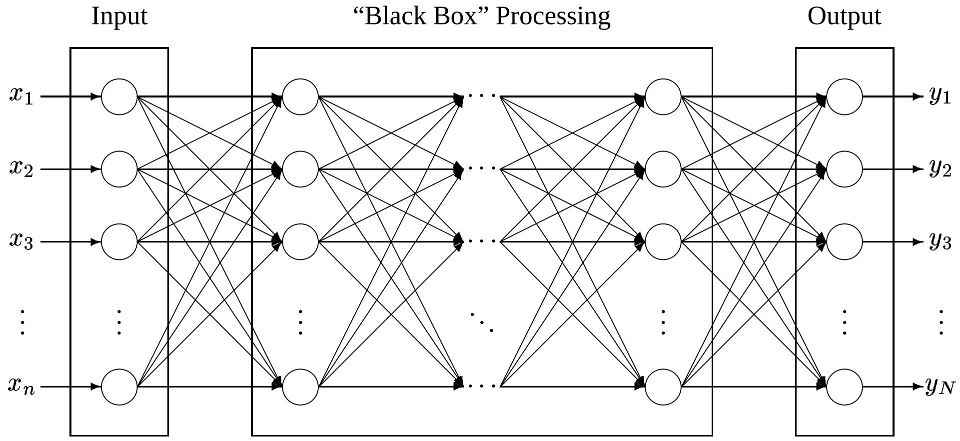

Figure 5: General feed-forward network

6 Classification

In order to find out what the user wants, a BCI system has to *classify* the preprocessed data. This means that the system does not attempt to *understand* the user's intentions, but it "compares" the data symbolizing a segment to representatives of a limited number of classes, and selects the class matched best. One way to implement the classification module is to employ Artificial Neural Networks[7] (ANNs) as described in e.g. (Jandó *et al.* 1993) and (Felzer 1994).

Those networks are designed in accordance with the brain as natural prototype, and there are numerous different architectures reported in the literature. Like their biological counterpart, they consist of a number of interconnected simple processing units, i.e. artificial *neurons*.

The units are organized in layers, and most ANNs consist of an input layer, an output layer, and one or more layers in between. The ANN works like a "black box", taking the input vector and generating an output vector, where the state of the neurons in the intermediate layers is invisible or "hidden".

The connection between two units is typically associated with an adjustable weight (the exact value of which is found during an initial training or *learning* phase), and the output of an artificial neuron (which is propagated to multiple successor neurons) is a function of the weighted sum of its inputs.

The network's task is to provide the correct answer (in the form of the N-dimensional output vector) for a request (the n-dimenional input or *feature* vector). The input vector ($\in \mathbb{R}^n$) is a pattern to be classified (e.g. a certain representation of a preprocessed EEG-segment), and the output vector – (in the classification context mostly) a "1-of-N vector" – encodes which of N classes the input pattern belongs to, meaning that one output neuron (the one standing for the recognized class) yields a value of (or close to) 1.0, while all others yield 0.0 (or a value close to that).

Three major classes of neural classification architectures can be distinguished: those based on the principle of Supervised Learning, those employing Unsupervised Learning and approaches containing elements of both learning paradigms. The following deals with these three network categories, with the primary focus on *feed-forward* networks, i.e. networks without any feedback loops, where the data is "fed" into the input layer and only *passed forward* during processing (see fig. 5). At the end of this section, it will be explained why *recurrent* networks – with feedback loops – are of particular interest in the context of BCIs.

[7] Genetics-based Machine Learning (GBML, see Pattichis and Schizas 1996, Palaniappan *et al.* 2000) is another possibility, but will not be discussed in this report.

6.1 Supervised

In Supervised Learning, the classification result (the "desired output") is known for several sample input patterns, and the goal of the weight adjustment in the training phase is to associate each of those patterns with its corresponding output class. Due to the fact that ANNs always produce two "similar" outputs for two "similar" inputs, the effect of the training phase is that also unknown input vectors can be mapped onto useful output vectors, provided the unknown pattern is not too "dissimilar" to all training patterns.

In other words, Supervised Learning means programming – i.e. adjusting the weights – by presenting examples, and an ANN *generalizes* from those examples when confronted with new, unknown input vectors during "usual operation", i.e. in the so-called *recall* phase.

A well-known algorithm for Supervised Learning is the backpropagation learning algorithm (Rumelhart *et al.* 1986*a*, Rumelhart *et al.* 1986*b*), which uses *gradient descent* to minimize the error between desired and actual output vectors for all of the training patterns. The training phase consists of a number of cycles through the training set, where one cycle comprises the calculation of an actual output vector in a forward-pass and the subsequent weight update in a backward pass for each of the training patterns. Training stops (and recall can start) when the overall error has reached a minimum.

6.2 Unsupervised

When using Unsupervised Learning, there are no "known" associations. The user still has a set of training patterns, but since there are no "desired" output vectors, there is no way to compute an "error", which could give a hint on how to adjust any weights. Instead, the net has to make these adjustments alone – *unsupervised* – by deducing characteristics inherent to the training set and partitioning the input space.

Typical networks contain one single hidden layer with so-called winner-take-all neurons. Each hidden neuron i is associated with an adjustable n-dimensional position (or *codebook*) vector $\vec{w}_i$ The input (or *feature*) vector $\vec{x}$ is compared to each position vector, and the hidden unit i_0 whose corresponding weight vector $\vec{w_{i_0}}$ is closer (in Euclidean space) to $\vec{x}$ than all other $\vec{w}_i$'s (the unit i_0 is also called *winning unit*, since it wins a sort of competition against the other hidden units) determines the networks's output[8].

In the training phase, the weight vector $\vec{w_{i_0}}$ of the winning unit is adjusted (by moving it towards the corresponding input vector), and after several cycles through the entire training set, the position vectors represent instances of classes or groups of input vectors. A 1-of-N-encoding of the winning unit leads to a mapping answering the question which input vectors belong to the same class, and which belong to different ones – thus defining a partition of the input space.

The learning algorithm descibed above is basically the one introduced by Kohonen (see e.g. Kohonen 1989), and in the "neural net community", the underlying architecture is therefore often simply called *Kohonen-network*.

6.3 Hybrid Approaches

As already stated above, hybrid approaches combine supervised and unsupervised training methods. One example is the so-called *Forward-only Counterpropagation Network (FCPN)*, introduced by Hecht-Nielsen (1987).

The FCPN consists of three layers of artificial neurons (or *units*) – an input layer, a (hidden or) classification layer, and an output layer. Input and hidden layers represent a Kohonen-network, while the connection weights from the hidden to the output layer are trained using a supervised learning rule (Grossberg 1969).

The idea is that the input vector is mapped onto a subclass of the input space (represented by the winning classification unit) which is then mapped onto an N-dimensional output vector. The output vector may either be a 1-of-N vector (symbolizing N output classes) or a general vector $\in \mathbb{R}^N$. In the former case, the second mapping simply represents a mapping from subclasses onto classes. In the latter case, the weight vectors between the classification layer and the output layer (which are the result of the supervised learning process) can be interpreted as the mean desired output vector of all those input vectors mapped onto the corresponding subclass.

So far for feed-forward networks. Now, the following subsection will demonstrate, what feedback loops might be good for.

[8] If there are two or more equally close position vectors, any one of the associated classification neurons will be declared to be the winner.

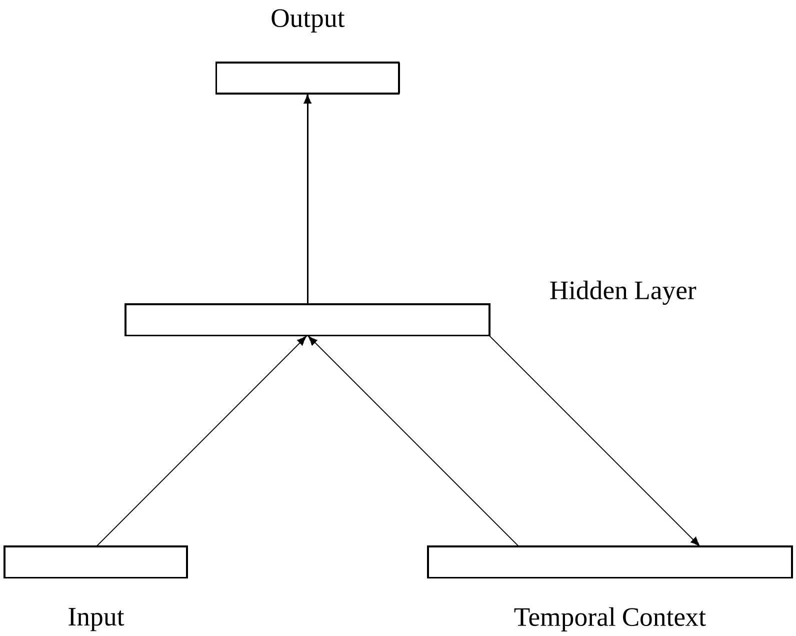

Figure 6: A Typical Elman-Network

6.4 Temporal Processing

An EEG trace is a particular kind of a time series, and it seems imaginable that a mental activity causes also characteristic *temporal* patterns. In other words, the way in which the signal varies over time might be important, too. Therefore, it does probably not suffice to study the EEG signal at isolated points in time. Examining *sequences* of feature vectors (from successive segments) might be a good idea – a method commonly known as *temporal processing* (see e.g. Felzer 1996, Hohm *et al.* 1996, Felzer *et al.* 1997).

One very intuitive way of realizing such a *short-term memory* is a so-called *Elman-Network* (Elman 1990, Kremer 1995). This ANN – depicted in fig. 6 – is a recurrent network, which consits of 4 (or, better, 3.5) layers, an input layer, an output layer, a hidden (i.e. invisible to the user) layer, and a context layer. In each step, the hidden layer is fed back to the context layer (of equal size), and the next state of the hidden layer units depends on the new input vector and the old hidden state. The context layer therefore captures the temporal structure of past inputs.

7 The BCI Output

The main topic of the previous sections was the direction "brain→computer". For the development of a BCI, one has to deal with the other way round, too. This does, of course, not refer to action potentials in neurons, artificially invoked by the computer, or similar science fiction stuff. In the context here, "opposite direction" means that – after having processed the input data and after guessing about the user's intention, the computer has to do something with this guess. In other words, some form of output has to be generated (by the computer) as a reaction to the user's brainwaves.

Most current approaches present the user with feedback by taking one of a limited number of actions, e.g. moving the cursor on a computer screen to the left or to the right, or revealing what the computer "believes" to have recognized (i.e. the result of the classification of the input data). This kind of BCI output does not provide the user with too much assistance, which means that the corresponding systems often are no ready-to-use tools. They merely demonstrate the principle of extracting information from the brainwaves of their users, and that's exactly what they're intended to do (e.g. Patmore *et al.* 1994).

Another possible BCI output is related to the selection of characters, which enables the user to write words and

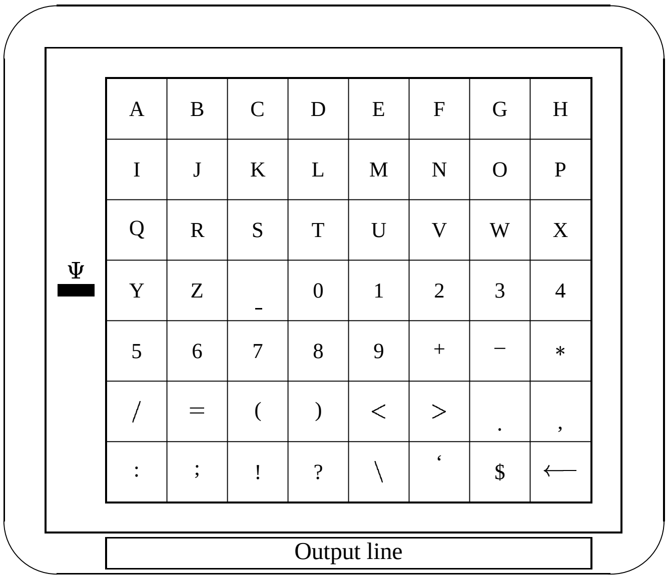

Figure 7: “Spellboard” Screen

letters – in order to compose an email, for example – by consecutively selecting single characters with the help of mental activities alone[9].

There are two different ways for the realization of such a *spelling device*. On the one hand, the system might have the user repeatedly chose between two sets of characters, which means that the user selects single characters in a binary search-like fashion (Birbaumer *et al.* 1999). On the other hand, the system might display a “keyboard” (like the one in fig. 7), and the user is expected to move a marker (here denoted with Ψ) on the screen over the desired character (an example – though based on EMG rather than EEG signals – can be found in0 Felzer and Freisleben 2000). In a modification of this second possibility, the system cyclically displays the characters of the keyboard – one by one – and the user’s task is to issue a significant mental answer, when the right character is shown.

The reaction of the system, i.e. the output of the BCI, will be the same in all of the above cases: the display of the selected character. By repeatedly executing this selection process, entire letters can be “typed” with the help of this *virtual keyboard* (this may take a while, though).

Finally, instead of directly operating a computer (by replacing the standard keyboard), a BCI could produce output commands for (computer-operated) external devices, e.g. by generating certain IR-signals in order to emulate a remote control, or by issuing commands moving the joints of a robot arm. Another example might be a system whose output controls an electrical wheelchair, thus enabling a paralyzed person to move “hands-free”, only with his or her brainwaves (see e.g. d. R. Millán *et al.* 1998).

8 Major Drawbacks

It should have become clear already that the development of a BCI is not at all trivial. There are a lot of drawbacks and problems one is confronted with. In this section, all of the problematic aspects mentioned throughout this report shall be collected. They can best be summarized with the help of the following keywords.

- Universality,
- Equipment,

[9]This can be a great help for severely handicapped people, who cannot use hands or voice to communicate with others.

- Sensitivity, and
- Timing Issues.

The former two terms refer to problems making the task of devising a BCI system very difficult and complicated, the latter two render that task as good as impossible – at least as far as certain kinds of applications are concerned. It will be explained in detail below, exactly what is meant with those keywords.

8.1 Universality

The development of a BCI requires knowledge and expertise in a lot of different disciplines. Biology, medicine, physics, and electrical engineering are the ones responsible for the correct measurement of the EEG, the electrode placement, the shielding against electromagnetic interference, and the selection of appropriate input signals. The theoretical implementation of preprocessing methods demands additional thorough knowledge in mathematics and computer science, as does the design of the neural net classifier. The software realization of the entire system – including data acquisition, online classification, and the generation of output control commands – is the right job for a decent programmer. Depending on the intended BCI output, various other disciplines, such as mechanical engineering or telecommunications, might join the list of involved domains.

Moreover, even if you have a team of experts in all of those fields, you are not *guaranteed* to find a solution for your particular BCI system. Detailed knowledge in biology and medicine for instance may definitely be helpful for finding optimal electrode positions, but it cannot *replace* the time-consuming trial-and-error search. In addition, the other three drawbacks detailed in the following still remain – also for a team of experts.

8.2 Equipment

The EEG has already been discovered in 1924 (by Hans Berger), and since then, scientists have asked themselves if it is possible to find a link between the EEG curves and the thoughts of its "originator". Before the advent of modern computers – which are more and more powerful, while becoming smaller and smaller (and getting less and less expensive) – the use of EEG was restricted to visual inspection by trained experts in application fields like epilepsy diagnosis or sleep analysis. Nowadays, it is possible to have a computer automatically analyze the EEG signals online, which makes the BCI application theoretically feasible.

However, in order to be successful, it is vital to have the newest possible technical equipment. This refers to the EEG machine, the processing machinery (the computer), and the output device linked up with the BCI system.

Since the EEG signals are so small and sensitive to noise (see below), the input signal can only be used when the measurement is very exact – as in a modern EEG machine. Besides, finding optimal electrode positions is much easier when 64 or sometimes even 256 channels are recorded simultaneously and compared afterwards than with an older EEG machine providing only 8 or 12 channels.

The processing equipment has to convert analog input values to digital, preprocess the data by applying FFT or the like, feed the preprocessed data through a multilayer neural network, and generate appropriate output commands according to the obtained classification result. At the same time, new input values have to be recorded and temporarily stored in memory for subsequent processing. All this has to be done fast enough to ensure a smooth operation, so employing a powerful computer is indispensable.

Finally, if a real output device (other than the computer, i.e. the output screen, itself) is to be used, a lot of additional hardware to interface it with the computer might be needed.

8.3 Sensitivity

The potential changes in the brain are extremely small, and the signal has to be tremendously amplified in order to be displayable. The problem with this is that noise is amplified, too. And, as two simple examples will illustrate: there can be a lot of noise!

The first example demonstrates the impact of electromagnetic interference coming from external sources. A modern (Germany-based) EEG machine possesses a built-in 50 Hz (which is the common AC frequency used in Germany) filter to reduce the effect of "humming" emanating out of the wall socket.

Fig. 8a depicts the EEG curve of a subject not concentrating on anything, just trying to relax. The only special feature here is that the 50 Hz filter is switched off. Although the subject's thoughts did not differ very much from the situation illustrated in fig. 4, the curve contains a lot of jitter, and the corresponding frequency spectrum (fig. 8b) reveals a huge peak at 50 Hz, which exceeds the activity peaks at all other frequencies.

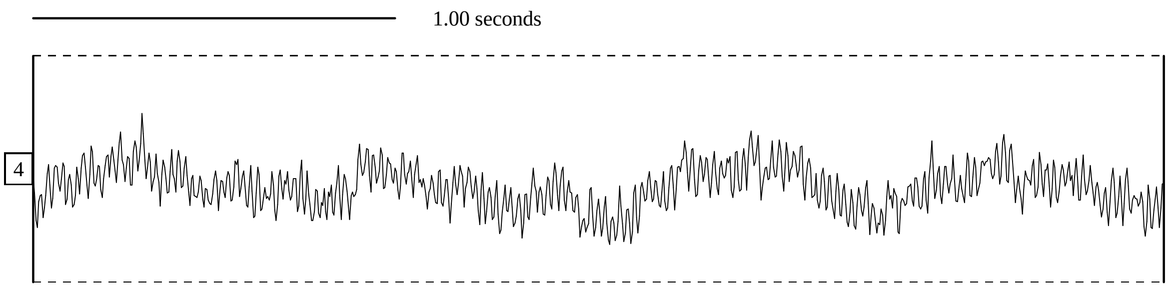

Figure 8a: Unfiltered EEG Curve of Channel 4

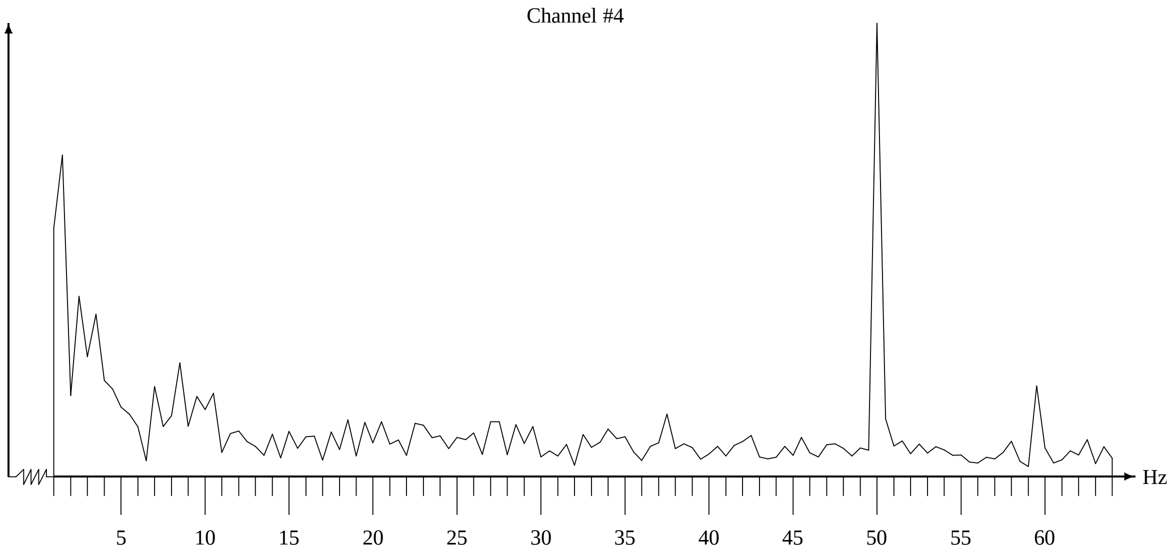

Figure 8b: Spectrum of Unfiltered EEG

The 50 Hz humming is just one external source of noise. It is easy to imagine that there is a lot of additional interference "in the air", all around us, e.g. coming from a moving elevator around the corner or a ventilator in the same room. Even another person passing nearby may influence the EEG curve considerably. And these interferences are generally unaffected by the built-in 50 Hz filter (see also Roberts *et al.* 1995)!

The second example illustrates the changes in the EEG caused by muscle contractions[10]. Fig. 9a shows the EEG of a relaxed subject at a rather coarse scale, i.e. small changes cannot be seen. However, performing a slight rotation of the head yields a huge eruption of activity (compared to "normal" EEG changes), as can be seen near the middle of the EEG reading.

[10] Since those changes are generally undesired, they are often called *artifacts*.

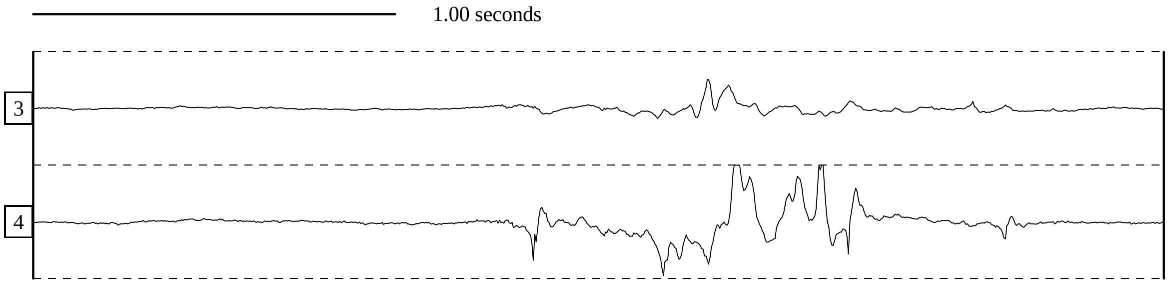

Figure 9a: EEG Reading ”Polluted“ by Head Movement (Note: Different Scale)

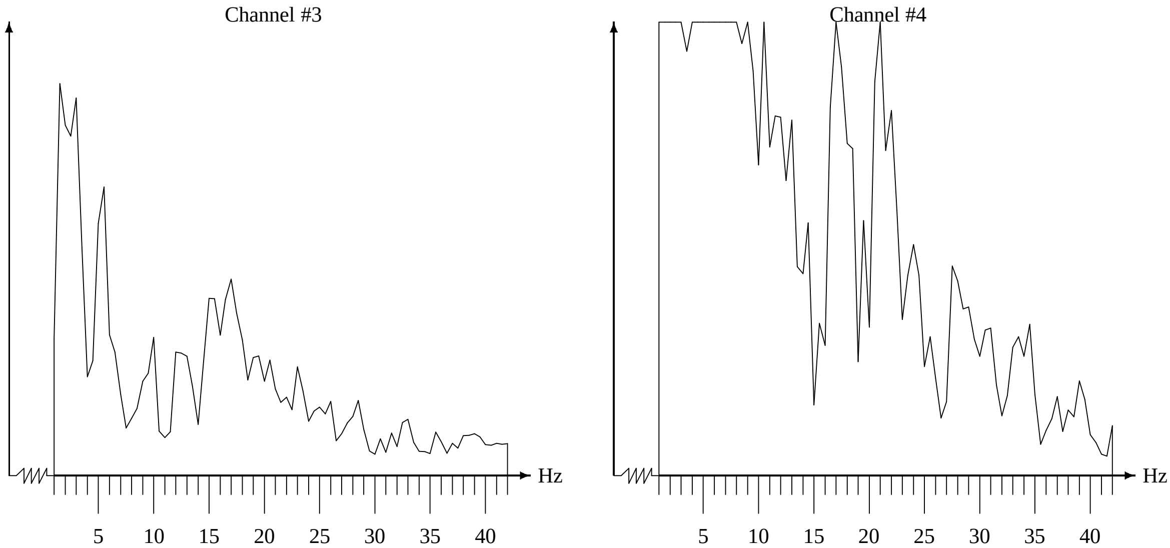

Figure 9b: Spectrum of ”Polluted“ Signal

The frequency spectrum in fig. 9b contains numerous peaks that have nothing at all to do with the subject's thoughts. Similar effects are caused by eye movement, eye closure, teeth clenching, frowning, varying facial expression and all other muscle contractions. Since the frequency peaks are totally unpredictable, they cannot be filtered out – the only way of dealing with those artifact-containing segments is to discard them (provided the goal is to use “genuine” brainwaves). Therefore, any BCI which is not bound to clinical conditions, i.e. with a subject sitting perfectly still in a shielded room, fully concentrating on the communication with the computer, not distracted by anything, is virtually impossible to construct.

8.4 Timing Issues

Online processing of data in a BCI system is subject to (at least) two time-critical constraints. To understand those, one has to recollect how a BCI acquires input data in general. The EEG is recorded continually, and at the same time, successive portions (also called *samples* or *segments*) – which may overlap in time – are selected for an input processing step.

The first timing issue in this respect refers to the time needed to process such an input segment – i.e. acqire the data, extract meaningful features, classify the feature vectors, and issue relevant feedback actions. As already mentioned when talking about the equipment, the computer has to be fast enough, which means the processing of a segment must be finished, when the next segment is ready. It also means that the algorithms chosen for the task have to be efficient enough.

The other question directly connected with the first has to do with the size of every single input sample. The longer such a segment is, the more time can be conceded to the computer to complete its processing. On the other

hand, the shorter the segments are, the faster the reply, i.e. if the BCI analyzes adjacent segments of $1s$ each, the user has to wait for (at least) an entire second to get an appropriate feedback as a reaction to his or her thoughts.

Especially this delay problem makes a brainwave-analyzing BCI inappropriate for a real-time application, such as a wheelchair steering system. If the wheelchair is heading for a staircase going down, and the user therefore wants the wheelchair to stop, he or she would most probably prefer an immediate feedback reaction with a very short delay. This brings us to yet another problem. A short delay means small input samples, and the neural net classifier is not able to extract useful information from too short segments.

Nevertheless, there *are* several *working* BCI systems, so it *can* be done (although with merely modest success), as will be seen below.

9 Current Approaches

This section describes some of the approaches adopted by developers of BCI systems today. It will become clear that it is possible (in principle!) to use the brain as some sort of communicative organ for “telling” a computer what to do. One has to bear in mind though that all of those successful approaches require the subject connected with the EEG machine to stay in a stiff position – none of them tolerates (let alone assumes) the subject to move, to talk, or even to blink while operating the system. EEG segments containing artifacts caused by any of those actions are rigorously sorted out.

9.1 Mu Rhythm

The $8-12$ Hz activity over the central sensorimotor cortex – present in nearly all adults – is called the mu rhythm. According to (LaCourse and Wilson 1995), mu waves are almost constantly present when the subject is relaxed and disappear when the subject moves a hand or a finger of the contralateral side, i.e. mu waves disappear over the left brain hemisphere when the right hand is moved and vice versa.

In addition, humans can learn to modify the amplitude of the mu rhythm after prolonged training (on the order of weeks or months) with the help of mental activities alone. This is the starting point of the system described in (Wolpaw *et al.* 1991). Their idea is to take that amplitude – measured by only <u>one</u> pair of electrodes – and translate it into (one-dimensional) cursor movement.

The computation is pretty simple. It involves computing the FFT of the ongoing EEG (“online”), taking the square root of the power associated with the mu rhythm frequency range, and comparing the resulting value with adaptable voltage ranges. This leads to a trivial quantification (or *classification*) encoding the mu rhythm amplitude, and is directly translated into the movement of a cursor on a feedback video screen, where low amplitudes move the cursor down, while high amplitudes move it up (the magnitude of the upward or downward movement being part of the quantification, too).

Although the accuracy that can be achieved with this system is relatively high (in up to 95% of all cases, the system really does what the user wants it to do), it cannot serve as the basis for a practical device, since it is awfully slow. To cope with this problem, Wolpaw and McFarland (1994) tried to develop a multi-dimensional control. The idea was to record the EEG at two different sites on the scalp, hoping that subjects would be able to learn to intentionally vary the two mu rhythm amplitudes simultaneously and independently.

The projected system was much more practicable, since it possessed the potential to “emulate” a computer mouse to a certain extent. However, despite the correctness of the “independence hypothesis”, the outcome was not much more than a laboratory phenomenon, because the achieved accuracy did not exceed 70%.

Polak and Kostov (1997) also use mu rhythm as the basis for a cursor control device. Subjects can move a virtual object up and down on a computer screen by issuing various mental activities during a time window delimited by the pressing of two manual switches.

9.2 Movement-Related EEG Potentials

The idea of (Kalcher *et al.* 1994) was to identify and detect those brainwaves that accompany slight motion of fingers or feet (*genuine brainwaves*, <u>not</u> electromyographic artifacts). Since the frequency band and the electrode

positions are not known in advance (as opposed to the mu rhythm), this amounts to recording a "complete" EEG and trying to somehow interpret and understand the brainwaves (while the approaches described in the previous subsection work the other way round, i.e. the subjects' brains are trained to produce output that can be easily interpreted).

During the operation of their system (the one described in (Pfurtscheller *et al.* 1996*b*) is basically the same as the one mentioned above, only limited to hand movements), the subject is told (with the help of audiovisual stimuli) which of three motions he or she is expected to perform. The corresponding EEG data is preprocessed and classified with a Learning Vector Quantizer (involving a certain kind of a Kohonen-network). The whole procedure is repeated for several sessions comprising a certain number of trials each, where the first session is used for training the neural net classifier, and the others for evaluation.

One neuromuscular finding states that the planning of a movement is associated with a certain kind of neuronal activity known as the "Bereitschaftspotential" (or "readiness potential", see Barreto *et al.* 1996). With this in mind and in addition to those sessions where subjects were supposed to physically perform motions, some sessions exclusively contained mental activity (see also Kalcher *et al.* 1996), i.e. the subjects were asked to merely concentrate on the motions (and to plan and imagine them mentally) without executing them. It is partially due to the aforementioned neuronal particularity that the accuracy did not suffer too much (at least not for the majority of the subjects).

In (Peters *et al.* 1998), the authors employ the same idea, but a new algorithm based on autoregressive modeling (see section 5). The achieved recognition rate of the neural net classifier of $92-99\%$ is pretty impressive. However, it involves rather idealized data (based on visual inspection of the recordings and removal of trials containing detectable artifacts), but nevertheless, the result demonstrates the potential power of EEG analysis in general.

Using movement-related potentials – comprising both, actual *and* imagined movements – as the basis for a BCI system is actually quite popular. The systems described in (Babiloni *et al.* 2000, Penny *et al.* 2000, Mayer *et al.* 2000) rely on the detection of hand movements, while (Lisogurski and Birch 1998, Mason and Birch 2000) concentrate on non-standard finger flexions signalling control commands. Other approaches exploiting movement-related potentials can be found in (Santos *et al.* 1999, Pineda *et al.* 2000).

9.3 Mental States

The brainwaves generated during the (execution or the) imagination of a movement characterize a special kind of state the brain is in. Anderson *et al.* (1994) examine more general mental states, not related with any physical activity, e.g. during the attempt of mentally solving a non-trivial multiplication problem.

In this approach, the EEG signals recorded during several different states are – like in *any* usual BCI system – chopped up into segments, and each segment is converted into a suitable representation. The data, i.e. the EEG representations, are fed into a three-layer feed-forward neural network trained with the backpropagation learning algorithm (Rumelhart *et al.* 1986*a*), and the task of the network is to associate the input segment with one of a limited number of mental states – possibly the one matching the subject's mental activity. Once the classification accuracy is high enough, the subject could use his or her brain as a communication channel by composing sequences of these states.

Unfortunately, despite the use of various preprocessing methods – including the Karhunen-Loève transform (an additional method involving eigenvectors, not described in section 5) and autoregressive modeling (see Anderson *et al.* 1995, Anderson and Sijerčić 1996), the average percentage of test segments correctly classified hardly exceeded 70%. Therefore, the approach is not (yet) appropriate for the real-time control of e.g. an electrical wheelchair (which requires a much more reliable communication).

Steuer *et al.* (1995) tried to detect mental states related to conceptual and pictorial thinking by analyzing the β band – with similar (i.e. *modest*) success rates. Ryu *et al.* (1998) employ time-frequency analysis as well as visual and auditory stimuli to distinguish between likes and dislikes (emotional "yes" and "no"). An improved classification accuracy in this approach is bought at the expense of an increased system delay of about one second (see also Ryu *et al.* 1999).

9.4 Slow Cortical Potentials (SCPs)

Birbaumer (1999) concentrates on so-called *Slow Cortical Potentials (SCPs)*. These are negative or positive potential shifts in the EEG lasting between 300 ms and several seconds. Because of their shape and their length, it is not too difficult to identify them – provided the classified EEG segments are long enough of course. Therefore, and because of the fact that humans (even completely paralyzed humans) can learn to voluntarily regulate them (Kübler *et al.* 1998), SCPs can be chosen as the basis of a BCI.

The system described in (Kübler *et al.* 1999) allowed the subjects to move a cursor horizontally or vertically on a computer screen with the help of self-regulated SCPs. After sufficient practice (i.e. training resulting in a $70 - 80\%$ accuracy), the system was extended with a language-support-program (LSP). The LSP enabled the subject to select characters – by repeatedly chosing between two groups of characters (where the groups get smaller and smaller, until both groups contain only one character each), involving moving the cursor towards a predefined goal when the desired character group is displayed – and thus "spell" words, phrases, or even entire letters (see also Perelmouter *et al.* 1999).

The resulting device gives locked-in patients with complete motor paralysis a chance to communicate with their environment and to have a social life (which was most probably not present before) by composing letters or emails. This work is therefore of invaluable merit since it helps to integrate people suffering from severe physical disabilities into the society. On the other hand, Birbaumer *et al.* (1999) admit that it took a certain locked-in patient employing their system (after prolonged training) about 16 hours (!) to write a message comprising approximately 500 characters. For this reason, the range of possible applications of the approach is somewhat limited.

9.5 Visual Evoked Potentials

In contrast to all of the approaches introduced above, the ones described in (Ming and Shangkai 1999, Middendorf *et al.* 2000) requires almost no training on the side of the subjects. The systems described there assume subjects to focus on blocks or virtual buttons flashing at different frequencies on a computer screen. The resulting frequency components are then extracted from the EEG signal recorded over the visual cortex. Since the eyes are occupied in these approaches, the number of possible applications is again very limited.

9.6 P300 Component

A positive waveform elicited by the rare events in a so-called "oddball paradigm" – involving frequent and infrequent external stimuli – occurring 300-450 ms after the stimulus is called a "P300 component" (or "P3", e.g Bayliss and Ballard 2000). Detecting this component (the generation of which is again "training-free" for the subjects) is the basis of the spelling device presented in (Donchin *et al.* 2000). Their idea is to cyclically highlight the rows and columns of a matrix containing the letters of the alphabet on a computer screen. The subjects concentrate on one character and are asked to watch out for the event, when the column and the row containing that particular character is highlighted. The subjects are therefore confronted with two classes of stimuli: a "rare" one related to the "correct" row and column and a "frequent" one related to the other rows and columns (see also Farwell and Donchin 1988).

By detecting the resulting event-related potentials, their system allowed "typing" at a rate of about 7.8 characters per minute with an accuracy of 80%.

10 Conclusion

The basic structure of a brain-computer interface (BCI) has been described in all its details. A BCI system records, preprocesses and analyzes the brain-electrical activity of a subject (with the help of an EEG machine), trying to identify and recognize characteristic patterns – often by employing a neural net classifier. The patterns have to be so that the subject can voluntarily, reliably and quickly generate them, <u>and</u> that they can easily and accurately be recognized (e.g. by the neural network). Analysis of the ongoing EEG then leads to a system output – sometimes merely needed as feedback for the user – generated on the basis of the results of the classifier.

The outcome is a way of communicating with a computer only by wilfully altering one's brainwaves. Therefore, a BCI is ideal for people suffering from severe physical handicaps (especially "locked-in" patients), since it gives them the chance to communicate with the environment (e.g. by composing emails) without the need to use their hands.

Besides, it should have become very clear that the task of developing a BCI is extremely difficult, since it requires a lot of basic knowledge in various different fields, and since it has to struggle with a number of serious problems concerning EEG recordings. Moreover, movement artifacts (e.g. from blinking) change the raw EEG or the frequency spectrum completely and thus render the recording useless (within the corresponding segment), so devising a BCI that allows physical activity is <u>more than</u> difficult – it is, in that case, virtually impossible.

On the other hand, this report has also shown that building a system which is controlled solely by the interpretation of brainwaves <u>can</u> indeed be done (provided the user renounces muscle contractions almost completely) and that examples of working BCI systems really <u>do</u> exist. Therefore, it has been proved empirically – after various findings supporting that assertion – that the brain-electrical activity is <u>not</u> a chaotic (or *accidental*) but a thought-related phenomenon.

Final Note

This report has grown out of the author's work on his dissertation during the last four years, which included the attempt to develop an own practicable brain-computer interface for controlling moving devices, like an electrical wheelchair (the results are described in detail elsewhere). When reading it, one might get the impression that some parts are merely a justification (or even an excuse) why he decided to use *muscle contractions* (rather than brain-electrical activity) as the basis for the interface. This is definitely no accident, but intended.

Acknowledgments

First of all, the author wants to thank Prof. B. Freisleben for many fruitful discussions and ample support during the work on his dissertation. In addition, he thanks Mr. Kandler from *NeuroKard* for supplying him with the EEG and EMG devices he needed (at no charge!) and for giving him useful hints on their operation. The author also thanks *Invacare Germany* for upgrading the electronics of his wheelchair and for helping him with all those hardware components necessary to realize a "computer-wheelchair interface". And last but definitely not least, the author would like to thank Prof. em. K. Offenloch, who initially brought his attention to BCI's and therefore got the whole project underway.

References

Alberts, B. et al. (1989). The Nervous System. In: *Molecular Biology of THE CELL*. Chap. 19, pp. 1059–1136. Garland Publishing.

Anderson, C. W. and Z. Sijerčić (1996). Classification of EEG Signals from Four Subjects During Five Mental Tasks. In: *Solving Engineering Problems with Neural Networks: Proceedings of the Conference on Engineering Applications (EANN'96)* (A. B. Bulsari, S. Kallio and D. Tsaptsinos, Eds.). Systems Engineering Association. Turku, Finland. pp. 407–414.

Anderson, C. W., E. A. Stolz and S. Shamsunder (1998). Multivariate Autoregressive Models for Classification of Spontaneous Electroencephalographic Signals During Mental Tasks. *IEEE Transactions On Biomedical Engineering* **45**(3), 277–286.

Anderson, C. W., S. V. Devulapalli and E. A. Stolz (1994). EEG as a Means of Communication: Preliminary Experiments in EEG Analysis Using Neural Networks. In: *ASSETS '94 – Proceedings of the First Annual ACM Conference on Assistive Technologies*. pp. 141–147.

Anderson, C. W., S. V. Devulapalli and E. A. Stolz (1995). Determining Mental State from EEG Signals Using Neural Networks. *Scientific Programming – Special Issue on Applications Analysis* **4**(3), 171–183.

Babiloni, F., F. Cincotti, L. Lazzarini, J. Millán, J. Mouriño, M. Varsta, J. Heikkonen, L. Bianchi and M. G. Marciani (2000). Linear Classification of Low-Resolution EEG Patterns Produced by Imagined Hand Movements. *IEEE Transactions On Rehabilitation Engineering* **8**(2), 186–188.

Barreto, A., A. M. Taberner and L. M. Vicente (1996). Classification of Spatio-Temporal EEG Readiness Potentials Towards the Development of a Brain-Computer Interface. In: *Proceedings of the IEEE Southeastcon '96: Bringing Together Education, Science and Technology*. pp. 99–102.

Bayliss, J. D. and D. H. Ballard (2000). A Virtual Reality Testbed for Brain–Computer Interface Research. *IEEE Transactions On Rehabilitation Engineering* **8**(2), 188–190.

Birbaumer, N. (1999). Slow Cortical Potentials: Plasticity, Operant Control and Behavioral Effects. *The Neuroscientist* **5**, 74–78.

Birbaumer, N., N. Ghanayim, T. Hinterberger, I. Iversen, B. Kotchoubey, A. Kübler, J. Perelmouter, E. Taub and H. Flor (1999). A spelling device for the paralyzed. *Nature* **398**, 297–298.

Brand, C. (2000). Implanted computer chip helps paralyzed man walk. *Manila Bulletin*. 23 March.

Carballido, J., A. Kostov and J. Martínez (1999). Enhancement Of EEG Control Signals In The Development Of A Brain-Computer Interface. In: *Proceedings of The First Joint BMES/EMBS Conference: Serving Humanity, Advancing Technology*. p. 445.

Chan, D. C. B., P. J. W. Rayner and S. J. Godsill (1995). Multi-channel blind signal separation by decorrelation. *Proceedings of the IEEE Signal Processing Society – 1995 Workshop on Applications of Signal Processing to Audio and Acoustics*.

Cody, M. A. (1992). The Fast Wavelet Transform – Beyond Fourier Transforms. *Dr. Dobb's Journal*.

d. R. Millán, J., J. Mouriño, M. G. Marciani, F. Babiloni, F. Topani, I. Canale, J. Heikkonen and K. Kaski (1998). Adaptive brain interfaces for physically-disabled people. *Proceedings of the 20th Annual International Conference of the IEEE Engineering in Medicine and Biology Society* pp. 2008–2011.

Diedrich, Dr. O. (1999). Mit Gedankenkraft – Elektrische Gehirnaktivität steuert Computer. *c't* pp. 296+. Issue 6/1999.

Dixon, T. L. and G. T. Livezey (1996). Wavelet-Based Feature Extraction for EEG Classification. In: *Proceedings of the 18th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, Amsterdam*. Vol. 3. pp. 1003–1004.

Donchin, E., K. M. Spencer and R. Wijesinghe (2000). The Mental Prosthesis: Assessing the Speed of a P300-Based Brain–Computer Interface. *IEEE Transactions On Rehabilitation Engineering* **8**(2), 174–179.

Elman, J. (1990). Finding structure in time. *Cognitive Science* **14**, 179–211.

Farwell, L. A. and E. Donchin (1988). Talking off the top of your head: Toward a mental prosthesis utilizing event-related brain potentials. *Electroencephalography and Clinical Neurophysiology* **70**, 510–523.

Felzer, T. (1994). Artificial Neural Networks, *MS Comprehensive Examination*. University of Colorado at Boulder, Department of Computer Science.

Felzer, T. (1996). Analyse menschlicher Bewegungssequenzen im Hinblick auf eine Übertragbarkeit auf Künstliche Lernende Systeme, *Diplomarbeit*. Technische Hochschule Darmstadt, Fachbereich Informatik.

Felzer, T. and B. Freisleben (2000). A new kind of Alternative Input Device for Human-Computer Interaction based on Muscle Control. (to appear).

Felzer, T., P. Hartmann, K. Hohm and P. Marenbach (1997). Motor Sequence Processing with an Artificial Learning System. In: *Biological and Artificial Computation: From Neuroscience to Technology – Proceedings of the International Work-Conference on Artificial and Natural Neural Networks, IWANN'97, Lanzarote, Canary Islands, Spain* (J. Mira, R. Moreno-Díaz and J. Cabestany, Eds.). Vol. 1240 of *Lecture Notes in Computer Science*. Springer–Verlag. Heidelberg. pp. 1307–1314.

Fey, J. (1995). Sägen am eigenen Ast?: Tagung 'Mind-Revolution: Schnittstelle Gehirn–Computer'. *c't* pp. 50+. Issue 4/1995.

Goelz, H., R. D. Jones and P. J. Bones (1999). Continuous Wavelet Transform For The Detection And Classification Of Epileptiform Activity In The EEG. In: *Proceedings of The First Joint BMES/EMBS Conference: Serving Humanity, Advancing Technology*. p. 941.

Grall-Maës, E. and P. Beauseroy (1998). Features Extraction For Signal Classification Based On Wigner-Ville Distribution And Mutual Information Criterion. In: *Proceedings of the IEEE-SP International Symposium on Time-Frequency and Time-Scale Analysis*. pp. 589–592.

Graps, A. (1995). An introduction to wavelets. *IEEE Computational Science and Engineering* **2**(2), 50–61.

Grossberg, S. (1969). Embedding fields: A theory of learning with physiological implications. *Mathematical Psychology* **6**, 209–239.

Hartmann, P., T. Felzer, S. Bleeck and R. W. W. Tomlinson (1996). Simulating Physiological Behaviour of Neurons. In: *Bio-Informatics and Pulspropagating Networks: BioNet'96 – Selected Contributions*. GFaI Berlin. pp. 39–44.

Hazarika, N., J. Z. Chen, A. C. Tsoi and A. Sergejew (1997). Classification of EEG Signals Using the Wavelet Transform. In: *Proceedings of the 13th International Conference on Digital Signal Processing*. Vol. 1. pp. 89–92.

Hecht-Nielsen, R. (1987). Counterpropagation networks. *Applied Optics* **26**, 4979–4984.

Hohm, K., T. Felzer and P. Marenbach (1996). Parameterized temporal sequences for motor control of a robot system. *MSCA'96, Crete, Greece*.

Isaacs, R. E., D. J. Weber and A. B. Schwartz (2000). Work Toward Real-Time Control of a Cortical Neural Prothesis. *IEEE Transactions On Rehabilitation Engineering* **8**(2), 196–198.

Jahnke, K. (1995). *Vorverarbeitung von EEGs mit einer Wavelet-Analyse zur anschließenden Verarbeitung mit einem neuronalen Netz, Diplomarbeit*. Technische Hochschule Darmstadt, Institut für Datentechnik, FG Mikroelektronische Systeme.

Jandó, G., R. M. Siegel, Z. Horváth and G. Buzsáki (1993). Pattern recognition of the electroencephalogram by artificial neural networks. *Electroencephalography and clinical Neurophysiology* **86**, 100–109.

Jasper, H. (1958). The Ten Twenty Electrode System of the International Federation. *Electroencephalography and Clinical Neurophysiology* **10**, 371–375.

Kalcher, J., D. Flotzinger, C. Neuper, S. Gölly and G. Pfurtscheller (1996). Graz brain-computer interface II: towards communication between humans and computers based on online classification of three different EEG patterns. *Medical & Biological Engineering & Computing* **34**, 382–388.

Kalcher, J., D. Flotzinger, S. Gölly, C. Neuper and G. Pfurtscheller (1994). Graz Brain-Computer Interface (BCI) II. In: *Computers for Handicapped Persons* (W. L. Zagler, G. Busby and R. R. Wagner, Eds.). ICCHP'94. Springer–Verlag. pp. 170–176.

Kennedy, P. R., R. A. E. Bakay, M. M. Moore, K. Adams and J. Goldwaithe (2000). Direct Control of a Computer from the Human Central Nervous System. *IEEE Transactions On Rehabilitation Engineering* **8**(2), 198–202.

Klinke, R. and S. Silbernagl (1996). *Lehrbuch der Physiologie*. 2 ed.. Georg Thieme Verlag. Stuttgart, New York.

Ko, C.-W., Y.-D. Lin, H.-W. Chung and G.-J. Jan (1998). An EEG Spike Detection Algorithm Using Artificial Neural Network With Multi-Channel Correlation. In: *Proceedings of the 20th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*. Vol. 20. pp. 2070–2073.

Kohonen, T. (1989). *Self-Organization and Associative Memory*. Springer–Verlag.

Kotchubey, B., U. Strehl, S. Holzapfel, V. Blankenhorn, W. Fröscher and N. Birbaumer (1999). Negative potential shifts and the prediction of the outcome of neurofeedback therapy in epilepsy. *Clinical Neurophysiology* **110**, 683–686.

Kremer, S. C. (1995). On the Computational Power of Elman-Style Recurrent Networks. *IEEE Transactions on Neural Networks* **6**(4), 1000–1004.

Kübler, A., B. Kotchoubey, H.-P. Salzmann, N. Ghanayim, J. Perelmouter, V. Hömberg and N. Birbaumer (1998). Self-regulation of slow cortical potentials in completely paralyzed human patients. *Neuroscience Letters* **252**, 171–174.

Kübler, A., B. Kotchoubey, T. Hinterberger, N. Ghanayim, J. Perelmouter, M. Schauer, C. Fritsch, E. Taub and N. Birbaumer (1999). The thought translation device: a neurophysiological approach to communication in total motor paralysis. *Exp. Brain Res.* **124**, 223–232.

LaCourse, J. R. and E. Wilson (1995). Brainiac: A Brain Computer Link. In: *Proceedings of the Instrumentation and Measurement Technology Conference of the IEEE*. pp. 587–592.

Levine, S. P., J. E. Huggins, S. L. Bement, R. K. Kushwaha, L. A. Schuh, M. M. Rohde, E. A. Passaro, D. A. Ross, K. V. Elisevich and B. J. Smith (2000). A Direct Brain Interface Based on Event-Related Potentials. *IEEE Transactions On Rehabilitation Engineering* **8**(2), 180–185.

Lisogurski, D. and G. E. Birch (1998). Identification Of Finger Flexions From Continuous EEG As A Brain Computer Interface. In: *Proceedings of the 20th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*. Vol. 20. pp. 2004–2007.

Lusted, H. S. and R. B. Knapp (1996). Computersteuerung mit Nervenimpulsen. *Spektrum der Wissenschaft* pp. 72–78. Issue 12/1996.

Makeig, S., T.-P. Jung, A. J. Bell, D. Ghahremani and T. J. Sejnowski (1997). Blind separation of auditory event-related brain responses into independent components. *Proceedings of the National Academy of Sciences USA* **94**, 10979–10984.

Marchesi, B., Á. L. Stelle and H. S. Lopes (1997). Detection of Epileptic Events using Genetic Programming. In: *Proceedings of the 19th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*. pp. 1198–1201.

Mason, S. G. and G. E. Birch (2000). A Brain-Controlled Switch for Asynchronous Control Applications. *IEEE Transactions On Biomedical Engineering* **47**(10), 1297–1307.

Mayer, I. V., H. Takahashi and K. Sakamoto (2000). EEG Classification By Autocorrelation-Pulse In Left And Right Motor Imaginary Data. In: *Proceedings of the IEEE Signal Processing Society Workshop on Neural Networks for Signal Processing*. Vol. 2. pp. 821–830.

McFarland, D. J., L. M. McCane, S. V. David and J. R. Wolpaw (1997). Spatial filter selection for EEG-based communication. *Electroencephalography and clinical Neurophysiology* **103**, 386–394.

Middendorf, M., G. McMillan, G. Calhoun and K. S. Jones (2000). Brain–Computer Interfaces Based on the Steady-State Visual-Evoked Response. *IEEE Transactions On Rehabilitation Engineering* **8**(2), 211–214.

Ming, C. and G. Shangkai (1999). An EEG-Based Cursor Control System. In: *Proceedings of The First Joint BMES/EMBS Conference: Serving Humanity, Advancing Technology*. p. 669.

Mirbagheri, M. M., K. Badie, R. M. Hashemi, M. Golpayegani and A. Ahmadi (1992). A Neural Network Approach to EEG Classification For The Propose Of Differential Diagnosis Between Epilepsy And Normal EEG States. In: *Proceedings of the 14th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*. Vol. 6. pp. 2649–2650.

Mölle, M., L. Marshall, W. Lutzenberger, R. Pietrowsky, H. L. Fehm and J. Born (1996). Enhanced dynamic complexity in the human EEG during creative thinking. *Neuroscience Letters* **208**, 61–64.

Moreno, L., J. L. Sánchez, S. Mañas, J. D. Piñeiro, J. J. Merino, J. Sigut, R. M. Aguilar, J. I. Estévez and R. Marichal (1998). Towards a Knowledge based System for the Clinical evaluation of the Electroencephalogram and Visual Evoked Potentials. In: *Proceedings of the IEEE International Conference on Systems, Man, and Cybernetics*. Vol. 4. pp. 4069–4074.

Offenloch, K. and G. Zahner (1988). Computer aided physiological assessment of the functional state of pilots during simulated flight. In: *AGARD Conference Proceedings No. 490 – Safety Network to Detect Performance Degradation and Pilot Incapacitation*. North Atlantic Treaty Organization. pp. 1–9, Chapter 9.

Palaniappan, R., P. Raveendran, S. Nishida and N. Saiwaki (2000). Evolutionary Fuzzy ARTMAP for autoregressive model order selection and classification of EEG signals. In: *Proceedings of the IEEE International Conference on Systems, Man, and Cybernetics*. Vol. 5. pp. 3682–3686.

Patmore, D. W., W. L. Putnam and R. B. Knapp (1994). Assistive Cursor Control for a PC Window Environment: Electromyogram and Electroencephalogram Based Control. *Center On Disabilities Virtual Reality Conference 1994*.

Pattichis, C. S. and C. N. Schizas (1996). Genetics-Based Machine Learning for the Assessment of Certain Neuromuscular Disorders. *IEEE Transactions on Neural Networks* **7**(2), 427–439.

Pauli, P., H. Schleichert, L. E. Jr. Bourne and N. Birbaumer (1998). Effects of cortical polarization on mental arithmetic. *Cognitive Brain Research* **7**, 49–56.

Penny, W. D., S. J. Roberts, E. A. Curran and M. J. Stokes (2000). EEG-Based Communication: A Pattern Recognition Approach. *IEEE Transactions On Rehabilitation Engineering* **8**(2), 214–215.

Perelmouter, J., B. Kotchubey, A. Kübler, E. Taub and N. Birbaumer (1999). Language support program for thought-translation-devices. *Automedica* **18**, 67–84.

Peters, B. O., G. Pfurtscheller and H. Flyvbjerg (1998). Mining multi-channel EEG for its information content: an ANN-based method for a brain-computer interface. *Neural Networks* **11**, 1429–1433.

Pfurtscheller, G., D. Flotzinger, M. Pregenzer, J. R. Wolpaw and D. McFarland (1996*a*). EEG-based Brain Computer Interface (BCI) – Search for optimal electrode positions and frequency components. *Medical Progress through Technology* **21**, 111–121.

Pfurtscheller, G., J. Kalcher, C. Neuper, D. Flotzinger and M. Pregenzer (1996*b*). On-line EEG classification during externally-paced hand movements using a neural network-based classifier. *Electroencephalography and clinical Neurophysiology* **99**, 416–425.

Pineda, J. A., B. Z. Allison and Vankov A. (2000). The Effects of Self-Movement, Observation, and Imagination on μ Rhythms and Readiness Potentials (RP's): Toward a Brain-Computer Interface (BCI). *IEEE Transactions On Rehabilitation Engineering* **8**(2), 219–222.

Polak, M. and A. Kostov (1997). Development Of Brain-Computer Interface: Preliminary Results. In: *Proceedings of the 19th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*. pp. 1543–1546.

Polak, M. and A. Kostov (1998). Feature Extraction In Development Of Brain-Computer Interface: A Case Study. In: *Proceedings of the 20th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*. Vol. 20. pp. 2058–2061.

Poulos, M., M. Rangoussi and N. Alexandris (1999). Neural Network Based Person Identification Using EEG Features. In: *Proceedings of the IEEE International Conference on Acoustics, Speech, and Signal Processing*. Vol. 2. pp. 1117–1120.

Roberts, S. J., M. Krkic, I. Rezek, J. Pardey, L. Tarassenko, J. Stradling and C. Jordan (1995). The use of neural networks in EEG analysis. In: *Proceedings of the IEE Colloquium on Sleep Monitoring*. pp. 3/1–3/3.

Rumelhart, D. E., G. E. Hinton and R. J. Williams (1986*a*). Learning internal representations by error propagation. In: *Parallel Distributed Processing: Explorations in the Microstructures of Cognition* (D. E. Rumelhart and J. L. McClelland, Eds.). Vol. 1. MIT Press. Cambridge, MA. pp. 318–362.

Rumelhart, D. E., G. E. Hinton and R. J. Williams (1986*b*). Learning representations by backpropagating errors. *Nature* **323**, 533–536.

Ryu, C. S., Y. Song, D.-S. Yoo, S. Choi, S. S. Moon and J.-H. Sohn (1999). EEG-Based Discrimination Between Yes And No. In: *Proceedings of The First Joint BMES/EMBS Conference: Serving Humanity, Advancing Technology*. p. 444.

Ryu, C. S., Y. Song, S. H. Kim, I. Yi, J.-E. Kim and J.-H. Sohn (1998). A Time-Frequency Analysis Of The EEG Evoked By Negative And Positive Visual Stimuli. In: *Proceedings of the 20th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*. Vol. 20. pp. 2012–2015.

Saevarsson, G., J. R. Sveinsson and J. A. Benediktsson (1997). Wavelet-Package Transformation as a Preprocessor of EEG Waveforms for Classification. In: *Proceedings of the 19th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*. pp. 1305–1308.

Santos, T. O., R. Caetano, J. Moniz and A. C. Rosa (1999). Classification Of Movement Cognitive Potentials From EEG. In: *Proceedings of The First Joint BMES/EMBS Conference: Serving Humanity, Advancing Technology*. p. 449.

Schmidt, R. A. (1982). *Motor control and learning: A behavioral emphasis*. Human Kinetics Publishers. Champaign, Ill.

Skrandies, W. (1998). Evoked potential correlates of semantic meaning – A brain mapping study. *Cognitive Brain Research* **6**, 173–183.

Steuer, D., B. Schack, G. Grieszbach and W. Krause (1995). Classification of human cognitive processes by the use of an improved neural backpropagation network. In: *Proceedings of the IEEE International Conference on Neural Networks*. Vol. 5. pp. 2495–2500.

Törnig, W. and P. Spellucci (1990). Numerische Mathematik für Ingenieure und Physiker. Band 2: Numerische Methoden der Analysis, Kapitel 11: Interpolation und Approximation.

Vidal, J. (1973). Toward direct brain-computer communication. *Annu. Rev. Biophys. Bioeng.* pp. 157–180.

Wolpaw, J. R. and D. J. McFarland (1994). Multichannel EEG-based brain-computer communication. *Electroencephalography and clinical Neurophysiology* **90**, 444–449.

Wolpaw, J. R., D. J. McFarland and T. M. Vaughan (2000*a*). Brain-Computer Interface Research at the Wadsworth Center. *IEEE Transactions On Rehabilitation Engineering* **8**(2), 222–226.

Wolpaw, J. R., D. J. McFarland, G. W. Neat and C. A. Forneris (1991). An EEG-Based Brain-Computer Interface for Cursor Control. *Electroencephalography and clinical Neurophysiology* **78**, 252–259.

Wolpaw, J. R., N. Birbaumer, W. J. Heetderks, D. J. McFarland, P. H. Peckham, G. Schalk, E. Donchin, L. A. Quatrano, C. J. Robinson and T. M. Vaughan (2000*b*). Brain–Computer Interface Technology: A Review of The First International Meeting. *IEEE Transactions On Rehabilitation Engineering* **8**(2), 164–173.

Zhang, T., F. Yang and Q. Tang (1999). Wavelet Based Approach For Detecting And Classifying Epileptiform Waves In EEG. In: *Proceedings of The First Joint BMES/EMBS Conference: Serving Humanity, Advancing Technology*. p. 943.